04 - DEMONSTRATING THE EFFICACY OF A SIMPLIFIED CONCEPTUAL HYDROLOGICAL MODEL IN SIMULATING RAINFALL-RUNOFF DYNAMICS: A CASE STUDY OF THE MIKE HYDRO BASIN NAM MODEL APPLIED TO THE RIVER NEIRA CATCHMENT, SPAIN

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Abstract

Calibrating rainfall-runoff models is notably challenging especially within large catchments where significant variations in hydrological characteristics are pronounced. The main challenge associated with calibration pertains to the complexity of parameterisation in such a profoundly diverse catchment. One approach to address this challenge is to employ conceptual models with simplified structures that capture the dominant processes while reducing the parameterisation complexity. The present study demonstrates this concept through the application of the MIKE HYDRO Basin NAM (MHBN) model to the River Neira Catchment in Spain. The MHBN model falls into the category of models built upon a simple water balance accounting approach and a flow routing method. It relies on the adjustment of nine essential parameters to achieve its functionality. These parameters have been calibrated using data spanning from January 2013 to December 2018. To establish the model's robustness, its performance has been validated against a distinct dataset encompassing the period from January 2019 to August 2022. The calibrated and validated MHBN model effectively replicates observed discharge hydrographs, displaying a high degree of agreement with actual flow patterns. The water balance loss (%WBL) is 0.0 for the calibration period and 12.9 for the validation period, highlighting the model's efficiency in maintaining the catchment's water balance.

In addition to these assessments, two statistical indices, namely the Index of Agreement (IA) and the Efficiency Index (EI), were employed to assess the model's reliability. These metrics quantitatively confirm the remarkable performance of the MHBN model, validating its accuracy in replicating observed discharge patterns. For calibration, the EI and IA are 0.862 and 0.961, respectively. In the validation phase, the EI is 0.821, and the IA is 0.949.

In summary, the MHBN model has demonstrated that a simplified conceptual model with a limited number of parameters can still offer significant versatility in effectively simulating discharge patterns within the River Neira Catchment. By showcasing the effectiveness of a simplified hydrological model with a limited parameter set, this discovery indeed holds the potential to significantly impact the field of hydrological modelling. It not only assists modelers in selecting appropriate models that match their expertise but also enhances the broader application of hydrological modelling in various water resource management studies. This advancement can lead to more accurate assessments, better-informed decisions, and improved management of water resources, ultimately contributing to sustainable and efficient water management practices.

1. INTRODUCTION

Modelling of surface runoff within a catchment is essential for various hydrological applications, encompassing the assessment of water resource management scenarios, flood risk mitigation measures, urban drainage designs, catchment water quality modelling, and other practical utilities. Mechanistic hydrological models play a significant role in estimating runoff within catchments. These models can be primarily categorised into two fundamental types based on their representation of rainfall-runoff transformation processes: fully physically based models and simplified conceptual models (Sitterson et al., 2018; Refsgaard, 1997). Physically based models depict these transformation processes deterministically by incorporating the physical principles of mass, momentum, and energy conservation. Conversely, conceptual models utilise simplified mathematical relationships to represent the relevant hydrologic processes (Sitterson et al., 2018; Beven, 1989). The spatial scale for modelling catchment processes is another criterion for classifying hydrologic models into distributed models and lumped models. Distributed models account for the variation in influential characteristics such as vegetation, soil, and topography across the catchment, whereas lumped models assume homogeneity in these catchment characteristics. Conceptual models are typically associated with lumped models, while practical physically based models tend to be characterised by their distributed nature (Refsgaard & Knudsen, 1996).

Distributed hydrologic models require substantial data and involve complex parameter identification. These factors limit their suitability and practicality for operational use (Suryatmojo et al., 2013; Pereira, 2017; Ngoc et al., 2011). Furthermore, there is limited evidence suggesting that distributed models significantly enhance modelling efficiency. Consequently, the application of lumped rainfall-runoff (RR) models remains a valuable alternative (Sitterson et al., 2018).

Nowadays a wide array of lumped conceptual hydrological models, catering for diverse requirements, have become available (Golmohammadi et al., 2014). However, when considering the lumped conceptual hydrologic models, it is imperative to acknowledge that their parameters cannot be directly derived from observable catchment attributes. Therefore, model calibration becomes an essential prerequisite in such contexts. During the calibration process, model parameters are estimated to enable the model to closely replicate the hydrological characteristics of the catchment (Yapo et. al., 1998). Model calibration can be conducted either manually or automatically. In manual calibration, model parameters are iteratively adjusted using a trial-and-error approach, with visual assessment involving comparisons between observed and simulated discharge. Achieving an accurate and hydrologically reliable model through manual calibration poses challenges due to its reliance on the judgment of the modeller. Furthermore, this method is time-intensive, especially for modellers with limited experience. In contrast, automatic calibration employs computer-based techniques to adjust model parameters. Notably, in automatic calibration, there is the capability to explicitly evaluate the confidence level in the model's simulation. This offers a more efficient approach compared to manual calibration (Liu & Sun, 2010). However, automatic calibration using a single objective function often lacks the ability to comprehensively evaluate all the essential aspects of catchment simulation (Madsen, 2000). Hence, the significance of adopting a multi-objective calibration procedure in hydrological modelling is evident.

The objective of the current study is to evaluate the reliability of a conceptual lumped hydrological model in predicting river flows resulting from rainfall within the River Neira Catchment. To accomplish this objective, we employ the conceptual rainfall-runoff model "MIKE HYDRO Basin NAM (MHBN)" and calibrate its parameters using a multi-objectives strategy. Automatic model calibration is conducted using data from January 2013 to December 2018, while model validation took place from January 2019 to August 2022. The selection of these periods enables the dataset to be divided in a manner where 60% is utilized for model calibration, and the remaining 40% is reserved for testing the model.

2. STUDY AREA

The central focus of this study is on the River Neira Catchment, located within the northwestern region of Galicia, Spain, as shown in Figure 1. Covering an extensive area of 832.7 km², the catchment extends across latitudes 42°40'N to 43°04'N and longitudes 7°06'50"W to 7°32'40"W. The River Neira, extending over a length of 56 km, is situated within this catchment area and serves as a tributary to the River Miño, which in turn feeds into the Belesar Reservoir. The Belesar Reservoir catchment (4,326 km^2) situated at an elevation of 260 m above sea mean level, is distinguished by its unique climatic characteristics. These include temperate winters, cool summers, high humidity levels, extensive cloud cover, and consistent year-round rainfall.

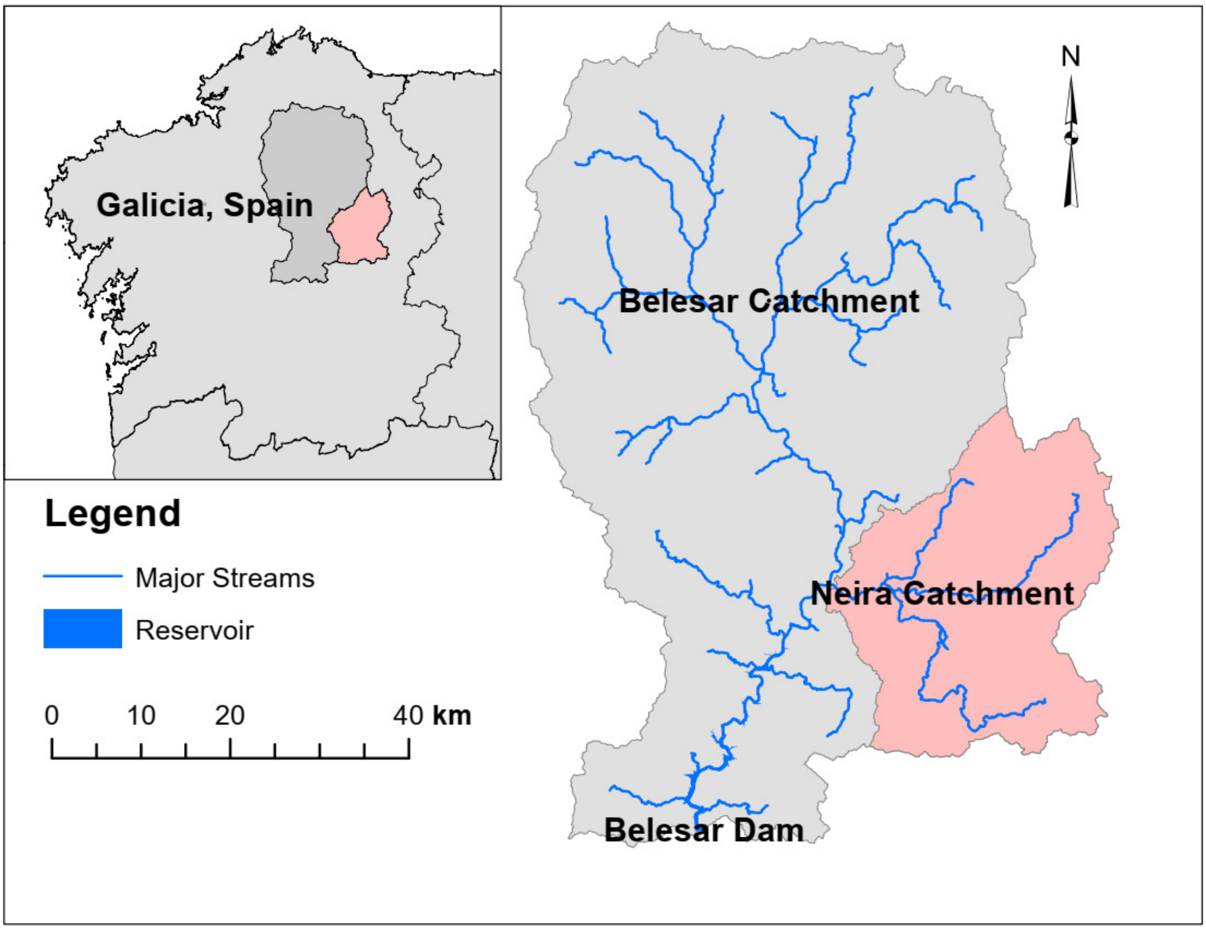

Figure 1: *Belesar and Neira Catchments*

3. DATA

The initial dataset comprises high-resolution satellite images (1 arc second) of the Digital Terrain Model (DTM), which have been obtained from the United States Geological Survey (USGS). This DTM underwent processing through ArcGIS version 10.8.2 to delineate catchment boundaries and to establish the stream network. Subsequently the MHBN model for this delineated catchment has been developed using historical time series data spanning from January 2012 to August 2022. This dataset includes records of precipitation, temperature, and evapotranspiration, all of which were acquired from the Agencia Estatal de Meteorología (AEMET), Spain's State Meteorological Agency. To ensure comprehensive coverage of data in the catchment, four meteorological stations within the Belesar Reservoir catchment were carefully selected. Initial steps involved identifying missing records and outliers within the precipitation, evapotranspiration, and temperature data. Filling gaps and adjusting values were then undertaken using the Arithmetic Mean Method. Additionally, where applicable, data from neighbouring meteorological stations were incorporated into the analysis. To determine the mean area weights, signifying the contribution of each station to the catchment, the Thiessen Polygon method was employed.

Furthermore, hourly streamflow data was collected from a streamflow gauging station located about 1 km upstream from the confluence of the River Neira with the River Miño. This streamflow data was sourced from the Spanish Water Information System, the Sistema Español de Información sobre el Agua (SIA).

4. MODEL DESCRIPTION

In this study, the hydrological model utilised is MIKE HYDRO Basin NAM (MHBN). NAM is derived from the Danish language and stands for "Nedbør-Afstrømings-Model," which translates to "precipitation - runoff model." The initial development of this model was carried out by the Department of Hydrodynamics and Water Resources at the Technical University of Denmark (Asger Nielsen & Hansen, 1973). Renowned for its reliability, the NAM hydrological model is extensively employed worldwide across various climatic conditions (Ahmed, 2010; Teshome et al., 2020; Rahman et al., 2012; Makungo et al., 2010; Singh et al., 2014).

Given its deterministic, lumped, and conceptual attributes (Agrawal & Desmukh, 2016), the NAM model simplifies input requirements as follows:

- Catchment information (identification of catchments, area of the catchments, basin composition of catchment)
- Meteorological data (precipitation, evapotranspiration)
- Hydrological data (discharge at the outlet of the catchments for model calibration and validation)
- Model parameters (time constants and threshold values for routing surface storage, rootzone storage and groundwater storage)

As a lumped model, NAM treats each catchment as a single entity and calculates average parameters. Additionally, NAM is conceptual, rooted in understanding the fundamental physical processes. The NAM model incorporates four different and mutually interrelated storage components within its structure: 1) snow, 2) surface storage, 3) lower zone or root zone storage, and 4) groundwater storage. This configuration is depicted in Figure 2, offering a visual representation of the NAM model structure. It includes the nine essential parameters outlined in Table I, which need to be calibrated using concurrent input and output time series.

In order to derive the optimum parameter values, it is necessary to establish calibration objectives that facilitate a successful automatic calibration using multiple criteria. The NAM model incorporates four distinct objective functions, each accompanied by its own computational procedure and theoretical justification as outlined by Madsen (2000). These objective functions encompass:

- Overall volume error (Agreement between the average observed and simulated catchment runoff)
- Overall root mean square error (Overall agreement of the shape of the hydrograph)
- Average root mean square error of peak flow events
- Average root mean square error of low flow events

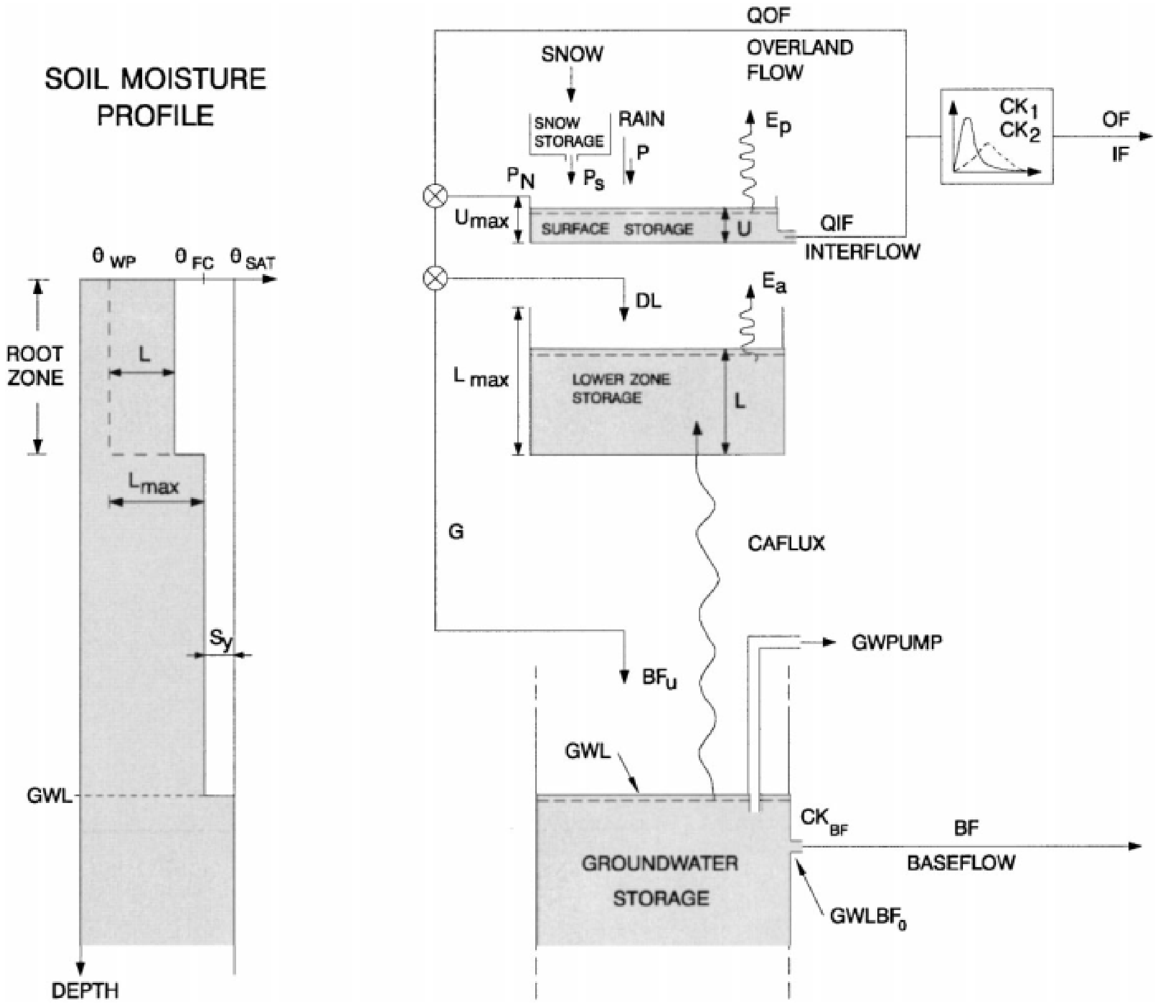

Figure 2: *Structure of NAM model* (Madsen, 2000; Willmott, 2013)

The evaluation of overall volume error involves measuring the water balance error or water balance (%WBL). Additionally, the quality of fit of the simulated hydrograph is evaluated through a normalised assessment of the overall root mean square error (RMSE), which is transformed and based on the coefficient of determination (R^2). The definition of %WBL and R^2 is as follows:

$$\%\mathrm{WBL} = \frac{\sum_{\mathrm{i=i}}^{\mathrm{N}} \mathrm{Q_{sim,i}} - \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{Q_{obs,i}}}{\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{Q_{obs,i}}} \text{ x } 100 \qquad (1)$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{N}} \left(\mathrm{Q_{obs,1}} - \mathrm{Q_{sim,1}}\right)^2}{\sum_{\mathrm{i=1}}^{\mathrm{N}} \left(\mathrm{Q_{obs,1}} - \bar{\mathrm{Q}}_{\mathrm{obs}}\right)^2} \qquad (2)$$

where Q_{obs} = observed value, Q_{sim} = simulated values and $\bar{Q}_{obs}$ = mean value of observed flow.

During the automatic calibration process, the optimal values for the nine model parameters (Table 1) are determined. Subsequently, in the second stage, the model is simulated using these refined parameter values, constituting the validation stage. A model is considered validated if its accuracy and predictive capacity in the verification period have been proven to lie within acceptable limits (Refsgaard & Knudsen, 1996).

5. MODEL PERFORMANCE

The evaluation of hydrological models can be conducted using visual analysis of graphs or statistical methodologies. The assessment of hydrological models can involve visual analysis of graphs or the application of statistical methods. The performance of the MIKE Hydro Basin NAM model, for instance, was evaluated using statistical measures, specifically the Index of Agreement (IA) (Willmott, 2013) and the Efficiency Index (EI) (Nash & Sutcliffe, 1970). The IA value ranges from 0 to 1, representing the agreement level between simulated and observed values. A value of 1 signifies perfect agreement, while 0 indicates no agreement. The Efficiency Index (EI) is utilised to detect model errors in long-term simulations, assessing the accuracy of simulated values in relation to observed values. An EI value of 1 indicates precise model performance. The definitions of IA and EI are as follows:

$$\mathrm{IA} = 1 - \frac{\sum_{i=1}^{N}\left(Q_{obs,i} - Q_{sim,i}\right)^2}{\sum_{i=1}^{N}\left(\left|Q_{sim,i} - \bar{Q}_{obs}\right| - \left|Q_{obs,i} - \bar{Q}_{obs}\right|\right)^2} \tag{3}$$

$$\mathrm{EI} = \frac{\sum_{i=1}^{N}\left(Q_{obs,i} - \bar{Q}_{obs}\right)^2 - \sum_{i=1}^{N}\left(Q_{obs,i} - Q_{sim,i}\right)^2}{\sum_{i=1}^{N}\left(Q_{obs,i} - \bar{Q}_{obs}\right)^2} \tag{4}$$

6. RESULT AND DISCUSSION

Figure 3 illustrates a comparison between observed and simulated streamflow hydrographs at the river flow gauge location during the calibration period, from January 1, 2013, to December 31, 2018. The model exhibits a highly successful calibration, signifying its ability to accurately predict streamflow and efficiently capture the overall trend. Corresponding hydrographs for the validation extending from January 1, 2019, to August 31, 2022, are presented in Figure 4. The validation results further confirm the model's precision in forecasting streamflow and representing the overall trend.

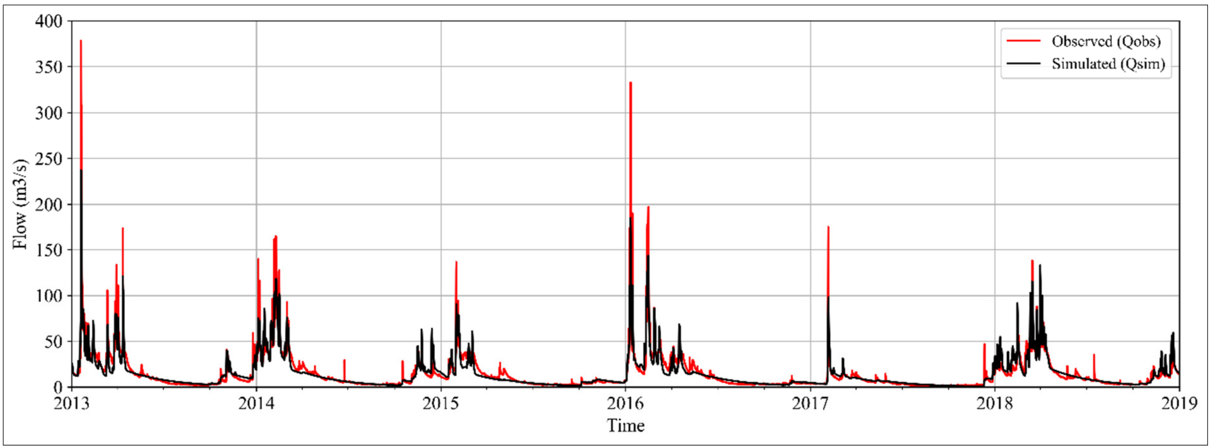

Figure 3: *Hourly flow during calibration period (January 2013 – December 2018)*

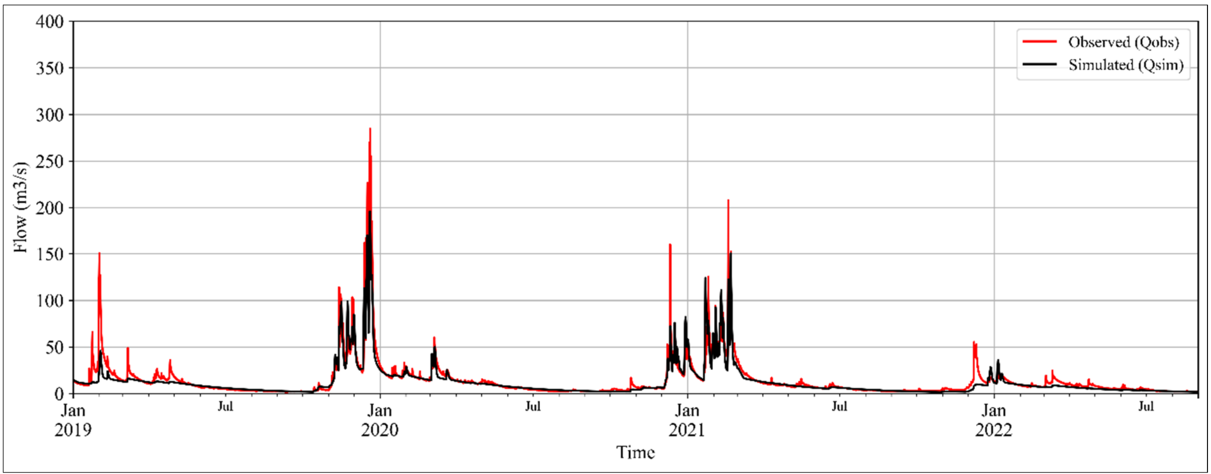

Figure 4: *Hourly flow during validation period (January 2019 – August 2022)*

Table 2 provides a comprehensive overview of hydrology-specific indicators and statistical metrics, encompassing %WBL (water balance loss), R^2, IA, and EI values, calculated during both the calibration and validation phases for the catchment. According to Lørup et al. (1998), a hydrological model is deemed valid when R^2 exceeds 0.80 and %WBL remains below 10%. Upon examination of Table 2, it becomes evident that the overall calibration phase satisfies this stipulated criterion. However, during the validation phase, %WBL falls below the specified threshold at -13.3%. While %WBL in the validation phase fails to meet the criterion, R^2, IA and EI values continue to demonstrate their adequacy, reaffirming the model's overall effectiveness in simulating hydrological processes.
A more detailed examination of individual years reveals that the criterion is met for all years except 2015 and 2018 in the calibration model, and for 2019 in the validation model. This observation suggests that the model encounter challenges in accurately capturing abrupt peaks, particularly during the initial year, despite the inclusion of a warm-up period of 365 days for the model. Nevertheless, the other essential statistical metrics, namely R^2, IA, and EI values, maintain satisfactory levels throughout the entire simulation periods. This could be attribute to the focus in calibration on specific objective functions, such as overall volume error and overall root mean square error. When considering peak flows as the objective function during calibration, %WBL values tend to exceed acceptable threshold.

7. CONCLUSION

The main objective of this study was to determine the optimum values for the nine MHBN model parameters (refer to Table 1) linked to the River Neira Catchment. These optimised values are of great importance in the concentration of a comprehensive hydrological model for the Belesar Hydropower Reservoir catchment. The modelling results affirm the efficiency of a lumped conceptual model, characterised by a limited number of parameters, in generating precise flow simulations in a substantial river catchment like the River Neira Catchment.

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Table 1: *MIKE HYDRO Basin NAM (MHBN) calibration parameters and optimize parameters*

Parameter	**Description**	**Model Parameter values**	**Parameter range**
U_{max} (mm)	Maximum water content in surface storage	19.998	5 - 35
L_{max} (mm)	Maximum water content in root zone storage	55.170	50 - 300
CQOF (-)	Overland flow runoff coefficient	0.560	0.1 - 1
TOF (-)	Rooting zone threshold values for overland flow	0.926	0 – 0.99
TIF (-)	Rooting zone threshold values for interflow	0.978	0 – 0.99
TG (-)	Root zone threshold value for groundwater recharge	0.000	0 – 0.99
CK_{IF} (h)	Time constant for routing interflow	278.634	100 - 1000
CK1,2 (h)	Time constant for routing overland flow	16.385	5 - 50
CK_{BF} (h)	Time constant for routing base flow Lower base flow/ recharge to lower reservoir	2060.340	200 - 4000

Table 2: *Model performance values of %WBL, R^2, EI and IA*

Year	**Q_{obs}**	**Q_{sim}**	**%WBL**	**R^2**	**EI**	**IA**
Calibration period (January 2013 – December 2018)						
2013	720.3	682.1	5.6			
2014	687.7	696.2	-1.2			
2015	426.9	374.9	13.9			
2016	676.1	641.5	5.4			
2017	222.2	241.2	-7.9			
2018	631.1	728.2	-13.3			
2013 - 2018	3365.7	3365.5	0.0	0.861	0.862	0.961
Validation period (January 2019 – August 2022)						
2019	760.0	630.3	20.6			
2020	457.3	442.2	3.4			
2021	555.1	508.5	9.1			
2022	187.3	154	21.6			
2019 - 2022	1959.7	1735.1	12.9	0.823	0.821	0.949

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